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Projections of long-term food security with R&D driven technical change—A CGE analysis

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ABSTRACT

In this paper, the impact of public R&D investment on agricultural productivity and long-term food security via R&D driven endogenous technical change is analysed. The findings show that R&D growth rates at the level reached in 2000s, particularly those for China, would not be expected any longer. Concerning the impact of projected R&D investments on agricultural productivity, it is found that endogenous growth rates of land-augmenting technical change are comparably lower than the standard exogenous rates used in long term projections of agri-food markets. This suggests that public R&D investments are not able to stimulate agricultural production to the levels that would be expected from the standard baseline outcomes.

1. Introduction

There are various challenges for reaching long-term sustainable agricultural production and food security. On the one hand, there are increased demand pressures resulting from ongoing population growth, improving living standards in developing countries and increased demand from non-food sources such as biofuels and other sources of renewable energy. On the other hand, there are constraints at the production side, due to limited space for expansion of agricultural land, climate change and migration of rural labour to urban areas. Recently the FAO estimated that food production needs to be increased with 60 percent to feed the global population of 9 billion people in 2050. Around 80% of the projected growth will have to come from intensification, predominantly an increase in yields through better use of inputs (Alexandratos and Bruinsma, [1]). Increasing agricultural productivity and crop yield is becoming even more important considering the fact that land and water resources are becoming scarce, which makes extensive agriculture more and more problematic.

Agricultural R&D investments in biotechnologies such as GMO represent a possible solution, in addition to the diffusion of existing technologies, for the food security challenge, especially in developing countries where cereal yields are still well below the global average level. Continuous investments in R&D are important from the perspective of all food security dimensions (FAO, [2]). The *availability* dimension of food security is associated with the physical supply of food. According to various scholars (such as Avila and Evenson, [3], Fuglie, [4], Pardey et al. [5], Alston, [6]), investments in R&D are important drivers of agricultural productivity and food availability. As Pardey and Alston [7] point out, U.S. agricultural R&D has fuelled productivity growth and food supplies not only in U.S. agriculture but also globally via R&D and technology spillovers.

The *accessibility* dimension of food security looks at the economic determinants of the access to food such as households' income and the evolution and variability of food prices. Particularly for the poor, who spend around 50% of their income on food consumption, changes in the prices of mayor staple crops such as rice, wheat and maize, can have a dramatic impact. The positive occurrence of the period of low agricultural prices in 1980s-1990s was predominantly achieved by R&D investments in better seeds and varieties during the Green Revolution.

The *utilization* dimension of food security refers mostly to the population's ability to obtain sufficient nutritional intake. As

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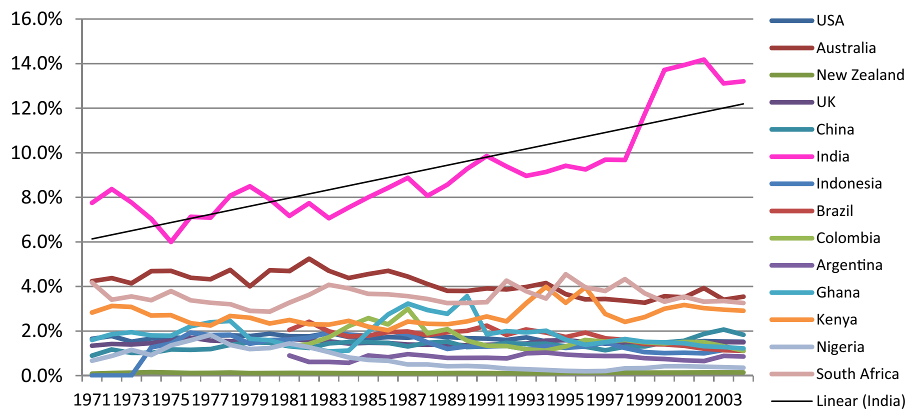

Fig. 1. Long-term evolution of the share of agricultural R&D expenditures in Gross Agricultural Output.
Note: R&D data compiled from various sources, data for Gross Agricultural Output taken from Fuglie dataset [4].

highlighted by Mogues et al. [8], the potential for agricultural investments to have significant and observable effects on health and nutrition is great. By increasing agricultural productivity, the corresponding farmer income gains can translate into better nutrition through greater calorie consumption and gains in dietary diversity, as well as improved health through a better ability to purchase medicine and access health services.

In view of this, the role of R&D investments as a key technology driver in achieving various dimensions of food security is undisputable. However, only limited attention is paid to R&D as a key technology driver in most of the leading assessment models that intend to project food security and corresponding changes in food production and prices. Recent work as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP) has examined differences in long run food price developments into the future through systematic model intercomparison (Nelson et al. [9], [10] and von Lampe et al. [11]). Von Lampe et al. in the overview paper concluded that a vast area of uncertainty is the accounting of technical progress in agricultural production. Robinson et al. [12] show that assumptions differ widely among models and are another important driver behind the different results. They conclude that more empirical research is needed to open the black box of macro and sectoral technical change. As a result, the ability to guide policy makers in defining long-term food security strategies is weakened.

The objective of this paper is to provide projections of agricultural production, food prices and other food security indicators towards 2050 using a global CGE model with endogenous R&D driven technical change in agriculture. The R&D driven productivity developments obtained in these projections will be compared with established yield projections used in key global impact assessment models and analyses.

The contribution of this research is twofold: i) methodological, by incorporating a dynamic accumulation of R&D stocks including region specific time lags and their links to agricultural productivity in a state-of-the-art CGE model, ii) policy-oriented, by exploring the possible directions of R&D investments worldwide and their impacts on agricultural productivity and consequently on food security. The explicit inclusion of the R&D sector and corresponding R&D stock accumulation in this CGE model is a distinctive feature from all other global impact assessment models used in food security projections.

The paper is structured as follows: chapter 2 contains the literature review which served as a basis for incorporating public R&D investments in the CGE model, as described in chapter 3. In chapter 4, outcomes of the model are analysed and chapter 5 concludes.

2. Literature review

2.1. Public agricultural R&D investments—high returns but long lags

There is rich empirical evidence on the effects of R&D investments on productivity with generally significantly positive results. According to the meta-analysis of 289 studies conducted by Alston et al. [13], the average returns on R&D in agriculture reached 82% (mean) and 44% (median). Recently, Hurley et al. [14] re-examined the rates of return in 372 separate studies from 1958 to 2011 and confirmed the positive evidence of R&D investments, although with lower returns than previously advocated. Similarly, Mogues et al. [8] presented updated evidence from country case studies focused on developing countries. They conclude that literature on public investments strongly suggests that returns to research and extension are significant. Next to that they point out three observations – i) higher R&D returns are found in R&D for shorter production cycles, such as field crops ii) higher returns have been found in R&D in Asia and developed countries and iii) R&D is associated with higher returns than agricultural extension.

Although public R&D investments undisputedly bring large returns, their benefits accrue with considerable lags, contrary to industrial research, which has a more short-term experimental character.[2] Thus, specific approaches must be adopted that allow for alternative accumulation of R&D investments to reflect this delay in the construction of knowledge stocks in agriculture. Trapezoidal lag models, polynomial-distributed lagged forms (PDL) and gamma lag distributions are the most common and recommended forms for modelling R&D stocks in agriculture. Thirtle et al. [15] comment, that the gamma distribution is of interest since it offers the smooth form of a trapezoid, which can be estimated rather than imposed. By fitting knowledge stocks calculated from alternative distribution specifications in a TFP regression, Alston [6] found that in a double log function, a gamma distribution with a maximum 50-year lag and peak after 24 years yields the best result. For the

[2] As Alston et al. [4] explains research and development might take 5–10 years before the variety is adopted, due to time spent on experimental trials and regulatory approvals. After the variety is adopted, farmers have to learn how to produce it, and consumers have to accept the new product innovation on the market. Therefore, the peak of benefits only comes 15–25 years after the initial investment. Eventually, the variety may become obsolete, as it may be less effective against evolving pests or diseases.

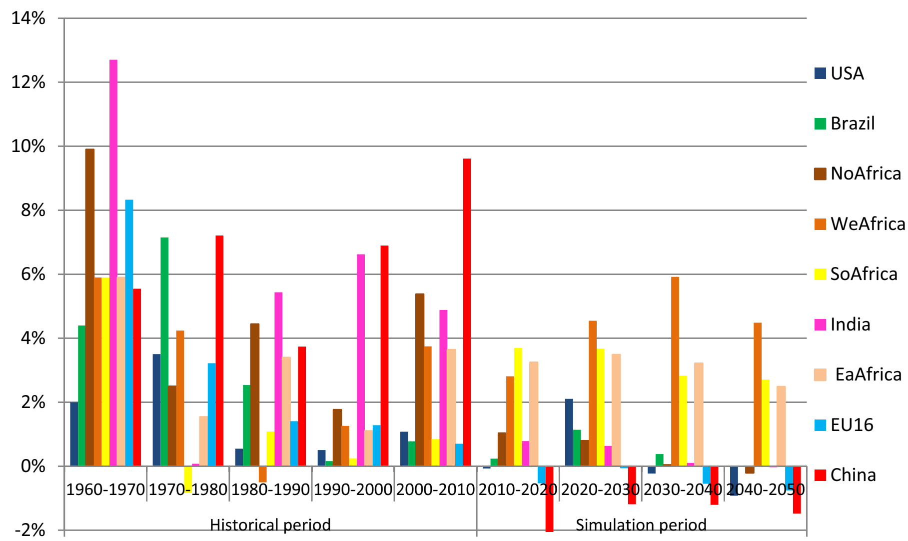

Fig. 2. Historical and projected annual growth rates of real R&D investments. Source: authors' calculations based on historical data and MAGNET output.

calculation of knowledge stock with this distribution, Alston used the following formulas:

$$RDstock_{i,t} = \sum_{k=0}^{50} b_k \times R_{i,t-k} \text{ where} \sum_{k=0}^{50} b_k = 1 \text{ and} b(k) = (k+1)^{\frac{\delta}{1-\delta}} \times \lambda^k \quad (1\text{–}3)$$

where $RDstock_{i,t}$ represents the accumulated knowledge stock per state, $R_{\text{i,t-k}}$ represents the R&D expenditures in lagged period *t-k*, b_k are gamma weights that sum to one, *k* is the maximum lag of the distribution and λ and δ are gamma distribution parameters.

Various studies have adopted the above-mentioned distributions in modelling R&D stocks. Recently, Andersen and Song [16] quantified the effects of cumulative R&D investments on **US agricultural multi-factor productivity**, adopting Alton's gamma distribution with 50 years lag and found positive evidence, with the elasticity of TFP with respect to R&D ranging around 0.3%. Sheng, et al. [17] tested 10 different alternatives of gamma, trapezoidal and geometric distribution for constructing knowledge stocks in **Australian agriculture** from 1953 to 2007. The authors concluded that the gamma distribution with a peak after 7 years and a lag of 35 years performed the best. Under this distribution, the estimated elasticity of TFP with respect to public R&D knowledge stocks was 0.23%, with an internal rate of return on public R&D reaching 28%. Similarly, Hall and Scobie [18] found a 17% rate of return on public R&D in **New Zealand** agriculture, using the perpetual inventory method, a Koyck transformation and a polynomial lag structure on annual data from 1927 to 2000. As for the **European agriculture**, similar studies that would quantify the effect of public R&D investments on productivity are scarce. A notable exception is found by Thirtle et al. [19] for the UK. The authors applied alternative distributions to the gamma distribution with lags of 25 years and their calculated elasticity ranged between 0.1–0.3%.

Concerning **developing countries**, a review of studies and calculated elasticities is presented in Ninn Pratt and Fan [20] who use a lag of 10 years and elasticities around 0.1% to simulate the optimal allocation of R&D investments across regions of Asia, Africa and Latin America. Their choice of parameters is largely based on the study of Thirtle et al. [19] that analysed the impact of research-led agricultural productivity growth on poverty reduction and calculated elasticities of R&D driven land productivity in the range of 0.3% for Asia, Africa and the Americas. A single country study for **India** was performed by Fan [21] who modelled R&D investments using a PDL functional form with a maximum lag of 13 years and derived an elasticity of 0.255%. Fan found that among all the rural investments considered in his study, agricultural research has the largest impact on urban poverty reduction in India per additional unit of investment. Other evidence from Asia was provided by Suphannachart and War [22] for **Thailand** who considered only seven year lags of R&D investments with corresponding elasticities ranging around 0.07%. A shorter lag of R&D investments is justifiable in developing countries, where research is often closer to extension. As argued by Alene [23] and [24], much of the R&D in **African agriculture** is of adaptive nature with a shorter gestation lag than would be the case for basic research. Applying a Second Degree PDL function with a 16 years lag, Alene quantified elasticity of Sub-Saharan African agricultural productivity with respect to R&D ranging around 0.2% (for TFP) and 0.38% (for value added per hectare). Alene concludes that agricultural R&D has significant effects on productivity in African agriculture with a rate of return of 33% per year and being thus a socially profitable investment in African agriculture. As for **Latin America**, a similar study was conducted by Bervejillo et al. [25] who found a gamma distribution with a 25 years lag and a peak in the 24th year to perform the best with corresponding elasticities of TFP with respect to public R&D stock in the range of 0.5%.

Finally, empirical evidence for countries of Central and Eastern Europe and the Former Soviet Block is almost non-existent. For the **Czech Republic**, Ratinger and Kristkova [26] found positive evidence of R&D stocks modelled by a gamma distribution with lags ranging from 7 to 15 years. They argued that shorter time lags compared to evidence from the UK or USA can be explained by the transition period which has seen a rapid upgrading of technologies, likely induced by the urgent need to enhance the competitiveness of agricultural production.

Most of the empirical studies mentioned above focus on the R&D effects of neutral technical change, assuming that all factors benefit equally from the innovation effort. However, there is evidence that some production factors benefit from technological change more than others: as shown by Acemoglu [27]. *Factor-biased* technical change might result from induced innovation (Hayami and Ruttan, [28]) that directs technical change towards the scarcer and hence more expensive production factor (for instance in Japan, specific crop varieties were developed that increase the productivity of land). The empirical tests that were developed to verify the presence of induced technical change have been widely applied, most importantly by Binswanger [29], Antle [30], and Huffman and Evenson [31]. More recently Thirtle et al. [32], studying induced innovation in USA agriculture, show that public research expendi-

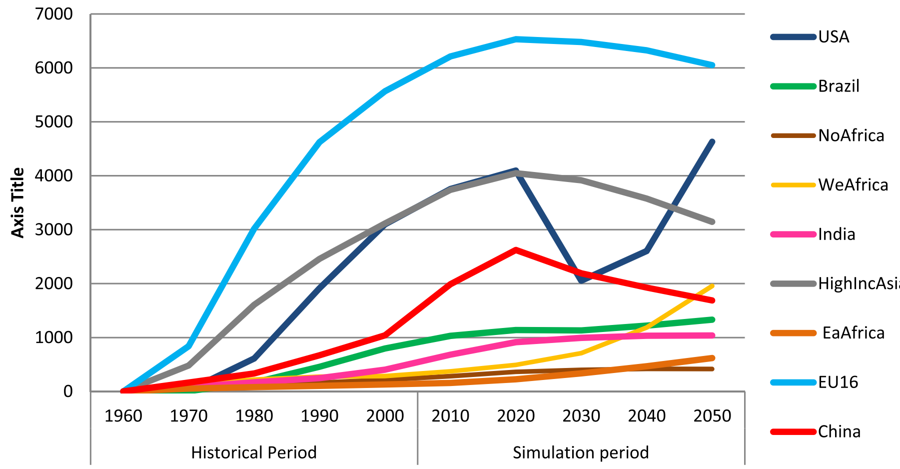

Fig. 3. Evolution of knowledge stocks in Baseline Vintage. Source: MAGNET output.

tures are important determinants of biased technological change. Moreover, the authors confirm that public R&D expenditures generate land-saving technical change, which is consistent with earlier work of de Janvry et al. (cit. in Thirtle et al.). Similarly, Piesse and Schimmelpfennig [33] in a study for UK agriculture confirm that public R&D in plant breeding has been land saving, while mechanical technology has been labour saving. They argue that it is the private sector that dominates the induced innovation process in machinery. The authors also conclude that the public sector's R&D impact takes longer than private R&D sector impact (18 years lag vs. 14 years), but is twice as large (long-run elasticity of 0.30 vs. 0.15), attaining this to the responsibility of the public sector for biological technical change. Wang et al. [34] explain that private research may be more applied than public sector research, and therefore may have a shorter lag structure compared with public R&D.

2.2. *Approaches for modelling R&D investments in CGE models*

Various approaches exist that incorporate the R&D sector into a CGE framework, such as linking R&D effects to Total Factor Productivity (TFP), as done earlier by Lejour and Nahuis [35] in the Worldscan CGE model or Verbic [36] for Slovenia, or via incorporating a cumulated R&D stock in the form of knowledge as a new production factor (as applied for instance by Kristkova, [37]). Fully dynamic Romer based endogenous growth CGE models incorporate effects via R&D production of capital varieties with a public goods feature and were applied by Ghosh [38] for Canada. The models of directed technical change are a further extension of the Romer style CGE models with two-variety capital sectors capturing the trade-off between improving productivity of one input versus others, as used by Popp [39] in the ENTICE model or Otto, Löschel, et al. [40]. These fully endogenous growth CGE models have typically forward-looking dynamic behaviour and are very strong in theory. On the other hand, certain features make these models less attractive for agricultural policy oriented analysis. First, a highly disaggregated production structure that captures all individual agricultural commodities may complicate the computability of the model, because of the inter-temporal solution. Second, the models are based on stylized assumptions that are not yet adequately supported by empirics. For instance, limited empirical estimates exist regarding the knowledge production function that links patents as an R&D output to R&D labour as an input. The same applies for the lack of empirical evidence for the value of the elasticity of substitution between capital varieties in the Dixit-Stiglitz production function, or between knowledge stock and capital and labour bundles in the CES production function. Third, a more fundamental issue is that in the above mentioned models the modelling of innovative effort is solely based on patented knowledge stock, while non-patented knowledge such as public agricultural R&D is not considered.

An interesting and empirically-based approach to modelling endogenous factor-biased technical change in a CGE model is presented by Parado and de Cian [41]. The authors link factor-augmenting technology parameters to spillovers embodied in the trade of capital goods. The parameters that link spillovers from trade to productivity are empirically estimated (see Carraro and de Cian, [42]).

Fuelled by an increasing interest to assess the impact of agricultural R&D investment on global agricultural production and food security, various global models have attempted to incorporate agricultural R&D investments in a number of approaches. Hoddinott et al. [43] and Perez and Rosegrant [44] apply the IMPACT model to assess the impact of investment in R&D on the prevalence of hunger and child malnutrition. To model technical change they take the elasticity of yields with respect to research expenditures on agriculture from the literature. Dietrich et al. [45] endogenise technological change in the MAgPIE model by relating the ratio of investment in (public and private) R&D (and infrastructure) and yield (using a 15 year lag), to a measure of land use intensity. The resulting elasticity of agricultural investment on yields of 0.30 is used to simulate the impact of investment in technical change on land use change. Finally, Baldos et al. [46], explore different public R&D investment scenarios on global food and nutrition security using the SIMPLE model. To model the relationship between agricultural R&D and technical change (measured as total factor productivity) in the model an elasticity of 0.25 is used for developed countries and 0.16–0.28 for developing countries. All three models (IMPACT, MAgPIE and SIMPLE) are partial equilibrium (PE) models that only simulate the agricultural sector and therefore are not able to address the impact of agricultural R&D investment on the wider economy (for instance through lower prices of agricultural commodities). Furthermore, although technical change is made endogenous to R&D investment in the PE model studies, R&D investment is still exogenous and modelled as a 'free' input that does not require resources (i.e. government budget in case of public R&D), which is not the case in reality. We aim to address these issues in this paper by using a CGE model that provides a picture of the total global economy.

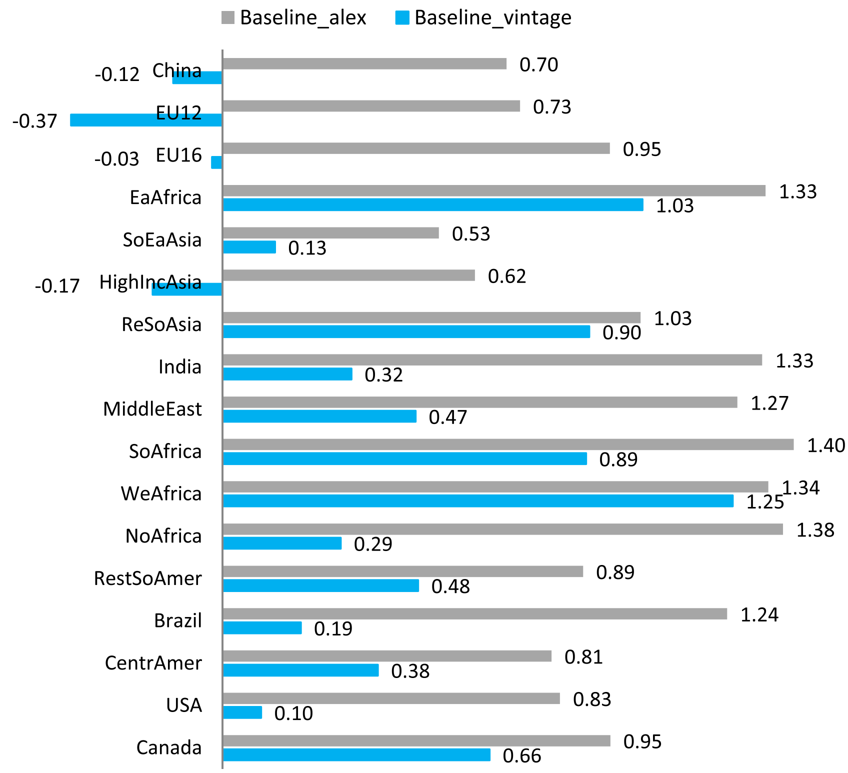

Fig. 4. Annual growth of land augmenting technical change across baselines (2010–2050). Source: MAGNET output.

3. Methodological approach

3.1. The Magnet CGE model

In this study, a sophisticated variant of the Global Trade Analysis Project (GTAP) model (Hertel, [47]) is employed, known as the Modular Applied GeNeral Equilibrium Tool (MAGNET – Woltjer, Kuiper et al. [48]). The CGE model MAGNET is an extended version of the GTAP (Global Trade Analysis Project) model, a widely used tool for global trade analysis. MAGNET is a neo-classical recursive dynamic multi-sector, multi-region computable general equilibrium (CGE) model that has been widely used to simulate the impacts of agricultural, trade, land use and biofuel policies on global economic development. The model has been applied to analyse the medium and long run effects of global and EU agricultural, trade, land use, and biofuels policies (Francois et al. [49], Van Meijl et al. [50], Banse et al. [51], Nowicki et al. [52], and Nelson et al. [9], [10]). The model is calibrated upon an input-output structure that explicitly links industries in a value added chain from primary goods, over continuously higher stages of intermediate processing, to the final assembling of goods and services for consumption. In common with the standard GTAP model, economic behaviour is 'demand' driven, with behavioural equations characterised by multi-stage neo-classical optimisation to segregate factor, intermediate and final demands into 'nests'. Producers are perfectly competitive and exhibit constant returns to scale technology. The equilibrium solutions are found by solving the demand, supply and price system of a large number of interacting factor and product markets that together cover the global economy. Medium to long run baselines are obtained by calibrating the model to exogenous macro assumptions of expected GDP and population growth. The main output of MAGNET is a set of economic indicators that describe the development of the global economy, including sectoral growth, employment, (food) consumption, prices and trade. An important feature of MAGNET, in comparison to the standard GTAP model, is that land use is made endogenous by including a land supply curve. A land supply curve is estimated using historical information on land prices and land supply as well as bio-physical data on actual land available that can be used for commercial purposes (e.g. crop land and pasture land versus parks) Van Meijl et al. [50].

For the analysis in this paper, MAGNET uses the GTAP database version 8, final release (Narayanan et al. [53]), which contains data on the economic structure of 140 countries for 2007. The sectoral division distinguishes 12 agricultural (land using) sectors available in GTAP at the highest level of detail, including paddy rice, wheat and other grains, various other crops and livestock and animal produce sectors as well as a (commercial) forestry sector, a fishing sector, manufacturing and services.

3.2. Incorporation of R&D-driven technical change in Magnet

In this paper, we make an important distinction between private and public R&D activities. We focus on public agricultural R&D targeted to major improvements of seeds and varieties in the style of the Green revolution, developed in specific publicly funded research institutes. In other words, we assume that public agricultural R&D is responsible for biological technical change, in line with the reasoning of Piesse and Schimmelpfennig [33]. Although one might argue that public R&D comprises more than just land-oriented research, investments in improving crop varieties are still the key focus of a publicly funded research.[3]

As opposed to private agricultural R&D where technology might be developed more "in-house",[4] public R&D requires a representation of a specific production sector and technology (for instance,

[3] This is also confirmed by Cowan et al. ([54], Table A1) who isolated R&D expenditures per category, and show that land research represents by far the largest category of R&D oriented research in the USA.

[4] Such as developing of farm machinery by John Deer or agricultural chemicals by Syngenta.

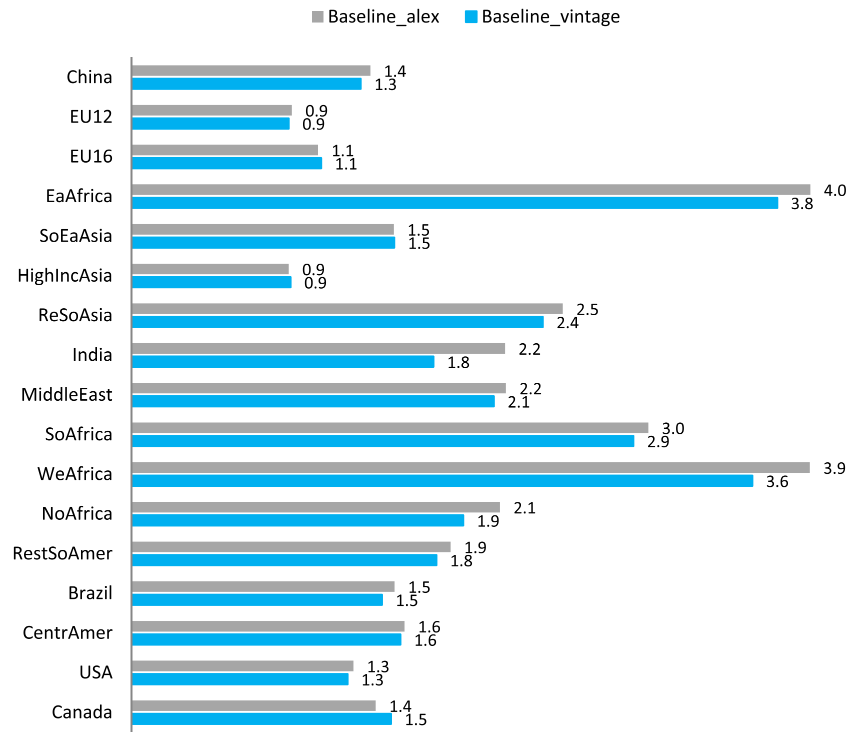

Fig. 5. Index of production volume of agrifood sector 2050 vs 2010. Source: MAGNET output.

independent CGIAR institutes developing new varieties). A second distinctive feature compared to private agricultural R&D is that the effects accrue only after long lags (ranging to 50 years). This explains why public R&D still represents the major financing source of agricultural research. As for private R&D, a shorter time lag is expected because of the more applied nature of research and also, intuitively, it is expected that private investors want to see their returns as soon as possible. For instance, in industrial business R&D, R&D stocks are typically built with a geometrical rate of 15% (Kumbhakar [55]), which means that in less than 7 years, the value of investment is totally depreciated. As for private agricultural R&D, the lag is mostly caused by the regulatory approvals, which may take up to 7 years in case of GMO crops (Qaim, [56]).

Given the often national focus and high level of stylization in most of the above mentioned approaches, we propose a global empirically based approach to link R&D with productivity coefficients in the function of Constant Elasticity of Substitution (CES) production structures in a global modelling framework. Besides being empirically based, the advantage of linking public R&D to productivity coefficients is that the agricultural sector benefits “freely” from public R&D investment but it is the government who pays for the expenditures (and the increased governmental consumption is reflected in reduced savings in the rest of the economy). Thus, the public goods component of agricultural R&D is well captured.[5]

Instead of linking R&D to total factor productivity consistent with a Cobb-Douglas production function, we consider factor-augmenting technical change that consists of an exogenous part and an endogenous part following the approach of Parado and de Cian [41], in line with a CES production framework. The endogenous part depends on domestic cumulative public agricultural R&D investments in all countries, the exogenous part is set to zero.

Following the assumption that the nature of public R&D research is mostly targeted to improvements in crop varieties, we link public R&D investments to land-augmenting technical change.[6] This assumption is also supported by the evidence of induced technical change by Thirtle et al. [32], and Piesse and Schimmelpfennig [33] cited above. Contrary to the land-augmenting effect of public R&D investments, private R&D investments, which largely result in improvements in mechanical technology, may have typically labour-saving effect on technical change.[7]

3.2.1. R&D data used for SAM disaggregation

Social Accounting Matrix (SAM) is a basic data structure that reflects all market transactions in an economy, which is used as a starting point for a CGE model in the base year. In line with our assumptions, a separate R&D sector was disaggregated from the sector of public services in the SAM. A simple procedure of applying the share of public R&D expenditures in the value of output of public services was applied to all cost components. This means that the public R&D sector employs the same share of skilled and unskilled labour as other public services. In most of the regions, the share of skilled labour reaches more than 50%, which is realistic.

In order to implement the R&D sector in MAGNET, various data sources were compiled to derive the value of public R&D expenditures for all 140 regions, namely i) Asti Public database for most of the developing countries [57], ii) OECD [58] and EUROSTAT [59] for European countries and iii) UNESCO Database [60] for the remaining countries. Next to that, data published in Pardey et al. [5] were used for agricultural R&D series for some developing countries. The

[5] The alternative and more common approach in the CGE literature is to include knowledge as a new production factor which results from cumulative R&D efforts. In this way, however, knowledge is part of the producers' cost minimization problem, meaning agricultural producers pay for R&D investment. This approach is more appropriate for modelling private R&D effects.

[6] Parallel to this research, empirical estimates have been carried out to quantify the direction of R&D in factor- augmenting technical change on the aggregate agricultural level.

[7] Inclusion of private R&D investments will be considered in the follow up research.

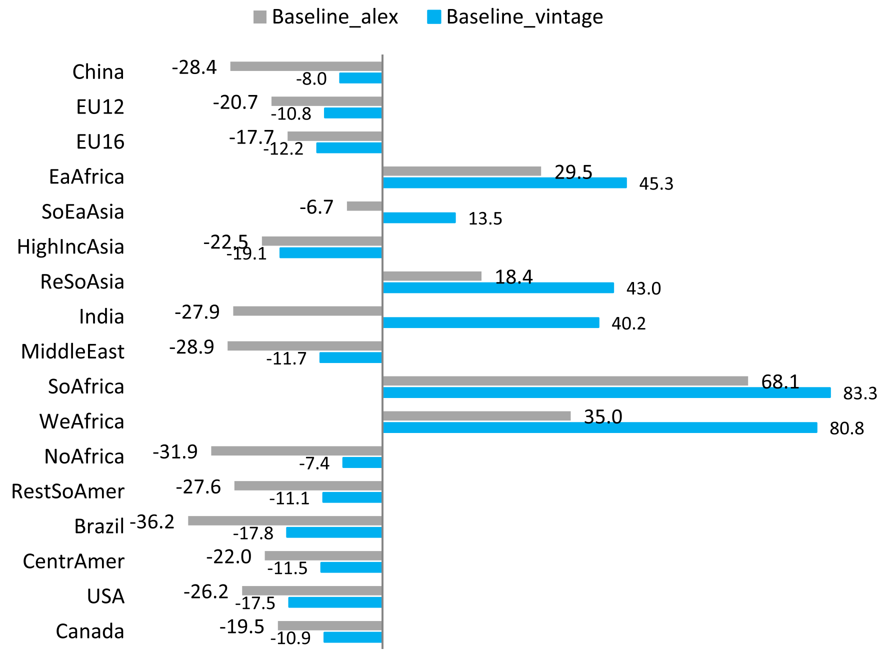

Fig. 6. Growth of real agricultural prices between 2010 and 2050 (%). Source: MAGNET output.

InsTepp Database Summaries provided in the paper of Pardey et al. [61] was used to obtain agricultural R&D expenditures for important EU countries which do not share the data with EUROSTAT, such as Germany, France, Spain or Italy. Finally, all values were converted from 2005 PPP dollars to 2007 current Dollars to homogenize with values of other variables in the SAM.

3.2.2. Modelling domestic R&D stocks in Magnet

Following the empirical evidence on the specific shape of the knowledge stocks distribution over time, a gamma distribution function was incorporated in MAGNET for building R&D stocks from public R&D expenditures. In line with the evidence in the literature, regions were grouped into six vintage groups. R&D investments in high income regions such as the USA exhibit the longest lags corresponding to the nature of the research (basic research prevails). On the other hand, developing regions are allocated to vintage groups with shorter lags due to the more adaptive nature of research (Tables 1 and Fig. A1). Similarly, the elasticity values vary with vintage groups and generally follow the pattern that the longer is the R&D distribution lag, the higher is the return and the elasticity of technical change with respect to R&D (the lags and obtained elasticities from neutral and factor-biased studies are comparable).

Given the choice of the vintage groups, R&D stocks in each region were reconstructed backwards from 1960 to 2010 using formulas 1–3. In the process of this calculation, a matrix of R&D vintages is constructed where each row indicates the distribution of annual investment over the production period (depending on the maximum lag) and each column indicates the contribution of t-k R&D investment to the current R&D stock.

Gamma weights and R&D vintage matrix for the period of the simulation horizon were aggregated to the length of the simulation periods. The growth of the cumulated R&D stocks from the gamma distribution is linked to land-augmenting technical change as shown in the following equation:

$$\mathrm{aland}_{j,r} = \mathrm{elasRD}_r \times \mathrm{rdstock}_r \qquad (4)$$

where *aland* represents the land-augmenting technical change parameter, which enters the CES production function, *elasRD* is the elasticity of *aland* with respect to R&D growth (values are reported in Table 1) and *rdstock* is the growth rate of domestic R&D stocks.

The CES functional form with land-augmenting technical change *aland* is provided in Equation 5:

$$VA_{j,r} = \left[\alpha \times \left(aland \times D_{j,r}\right)^{\left(\frac{\sigma KL,D-1}{\sigma KL,D}\right)} + (1-\alpha) \times \left(KL_{j,r}\right)^{\left(\frac{\sigma KL,D-1}{\sigma KL,D}\right)}\right]^{\left(\frac{\sigma KL,D}{\sigma KL,D-1}\right)} \qquad (5)$$

where VA_t stands for value added, D_t is land input, KL_t is capital-labour bundle (in case of a nested production structre), $\sigma_{KL,D}$ represents the elasticity of substitution between land and capital-labour input and α represents the share of each input in value added. Land augmenting technical change is defined as:

$$\frac{\partial VA\left(aland, D, KL\right)}{\partial aland} > 0 \qquad (6)$$

where value added grows with a constant level of land input.

3.3. Model aggregation, definition of scenarios and baseline assumptions

The production and region aggregation choices applied in MAGNET are provided in Table A1. There are 21 aggregated regions and 25 production sectors, from which 11 are primary agricultural sectors. Industry sectors are aggregated in low and high industry; services contain sectors of business services (oth_ser), public services (pub_ser) and the public agricultural R&D sector (rd).

Two scenarios are modelled with MAGNET. Each of them represents an alternative baseline scenario:

- Baseline ALEX: this is the usual baseline in which land-augmenting technical change is determined exogenously based on the historical growth rates of yields or exogenous scenario related assumptions, which means there is no R&D-driven technical change in the model.
- Baseline VINTAGE: In this baseline scenario, land-augmenting technical change grows according to the growth of the domestic R&D stock that respects the lagged distribution of R&D investments (vintage approach). The R&D investments are determined

Table 1
Parameters of the gamma distribution function of R&D stock accumulation per vintage group.

Group	Typical Regions	Max Lag years	Lambda	Delta	Elasticity aland to RD	Peak
A	USA	50	0.7	0.9	0.5	24
B	Australia and New Zealand	35	0.7	0.8	0.4	10
C	EU-15 and other High Income	25	0.6	0.85	0.4	10
D	EU-12 and Russian Federation	15	0.4	0.8	0.4	3
E	Latin America	25	0.7	0.9	0.3	24
F	Asia Pacific and Africa	15	0.5	0.8	0.3	5

Source: Authors elaboration.

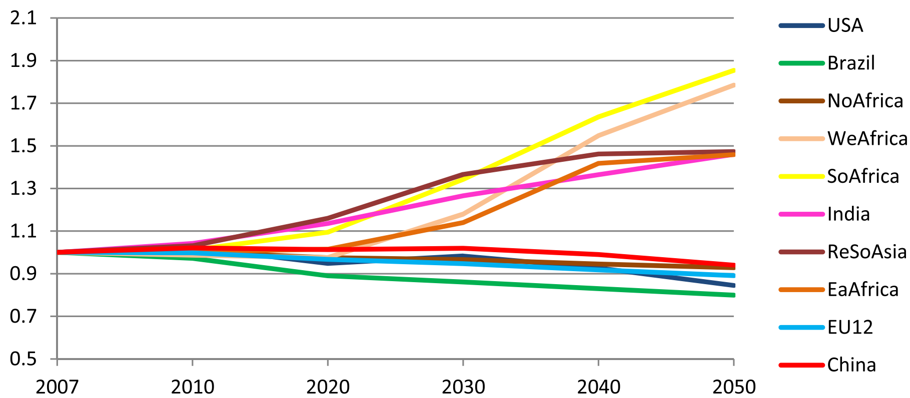

Fig. 7. Evolution of the index of real agricultural prices in the Baseline Vintage scenario. Source: MAGNET output.

as a fixed share of agricultural value added in the base year. This implies that R&D expenditures grow according to agricultural value added growth.

Fig. 1 plots long-term shares of R&D investments in agricultural production for countries where sufficiently long R&D data series are available. It can be noted that, except for India, the R&D expenditures seem to follow a constant share in agricultural production, which oscillates between 1% and 4% depending on the region, and which supports the assumption of a constant share of R&D expenditures in our model.

To develop the baseline scenarios we build on the Shared Socio-economic Pathways (SSPs), which have been recently developed to assess the impact of global climate change (Kriegler et al. [62], O'Neill et al. [63], and [64]). The SSPs are a set of plausible and alternative assumptions that describe the potential future socioeconomic development in the absence of climate policies or climate change. They consist of two elements: a narrative storyline and a quantification of key drivers, mainly population growth and economic development. For the assessment in the paper we only use one of the five SSPs, the so-called Middle of the Road (SSP2) scenario, which reflects a business-as-usual future. In this scenario, trends that are typical of recent decades continue in the future (O'Neill et al. [63]). There will be some progress towards achieving development goals but development of low-income countries proceeds unevenly. Most economies are politically stable with partially functioning and globally connected markets. Per-capita income levels grow at a medium pace on the global average, with slowly converging income levels between developing and industrialised countries. Intra-regional income distributions improve slightly with increasing national income, but disparities remain high in some regions. In the Baseline ALEX Scenario, the SSP2 consistent rates of exogenous land augmenting technical change (*aland*) are based on expert projections of yields into the future. In the Baseline VINTAGE Scenario they are determined endogenously from R&D stocks, following equation 4.

4. Impact of public R&D investments on productivity and food security

4.1. Projections of agricultural R&D investments

In this section, the evolution of R&D investments towards 2050 is analysed. Two interesting insights can be derived here – first a comparison of historical and projected growth rates and second, an interval in which future R&D investments might oscillate in each region. The evolution of real R&D investments towards 2050 that follow value added growth in agriculture is displayed in Fig. 2. Compared to the historical period (1960–2010), **R&D growth rates of China will be negative**, which is in line with the assumption of gradual slowdown of Chinese GDP growth. In the course of economic development of China and corresponding structural change, the demand for agricultural commodities relative to more processed goods will decline, which will result in a decline of agricultural value added towards 2050. Regions that might continue with high R&D investment rates are Sub-Saharan African states where rates could exceed 5% growth.

The evolution of domestic R&D stocks calculated as a weighted average of all past R&D investments using gamma distribution weights is provided in Fig. 3. In this Figure, R&D stocks are built from R&D investments following a growth rate of agricultural value added. Clearly, the biggest volume of public R&D stocks would be accumulated in the EU-16, also as the effect of the aggregation of 16 high income economies. After 2020, R&D stocks in the EU-16 will start to decline. It is also visible, that Chinese R&D stocks would grow dynamically in the first two decades benefiting from the excessive investments in 2000s, but after 2020, R&D stocks would gradually decline due to low investment levels projected in the future. An interesting evolution occurs in the case of the USA where R&D stocks grow progressively until 2020 but in 2030, their level falls by 50%. Such a dramatic decline is attributed to the long lag of R&D investments. Clearly, in the first two decades after 2000, the US agricultural sector benefits importantly from R&D investments carried out before the 1990s. In 2030, the slowdown of R&D investments in the USA after 2000s, as advocated in works of Pardey

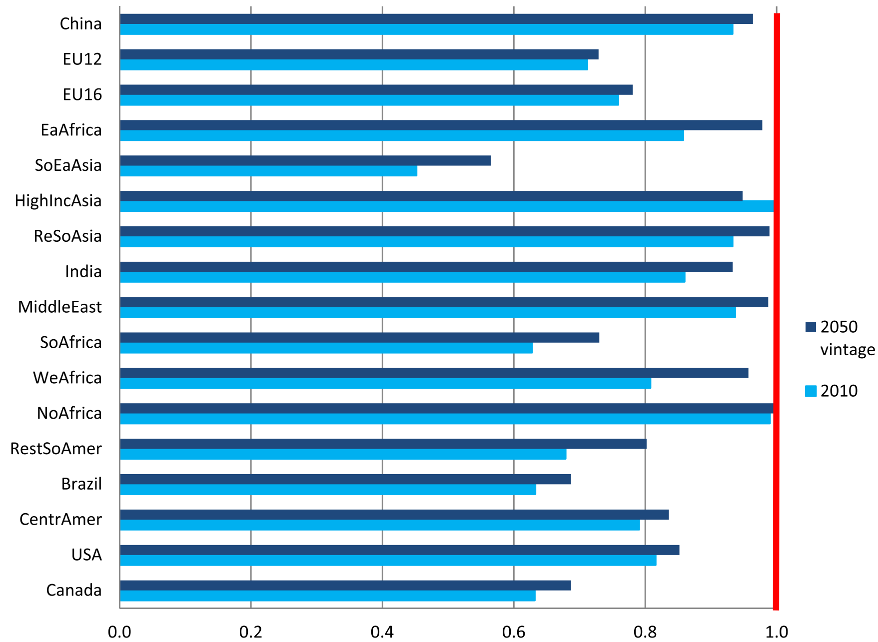

Fig. 8. Land pressure (demand of land to available agricultural land). Source: MAGNET output.

[62], and [67], is reflected in a serious drop of R&D stock. This is consequently reflected in the growth of agricultural prices driven by a decline of productivity, which in turn triggers an increased R&D spending and leads to an eventual recovery of R&D stocks. This is an important observation that shows that even if R&D investments are stimulated largely today, their effects in building R&D stocks will be seen only in the next 20–30 years.

Concerning Brazil and India, R&D stocks are projected to have a sustained growth along the whole simulation period, which is fuelled by agricultural GDP growth and shorter R&D lags.

4.2. Evolution of agricultural productivity with R&D-driven technical change

As explained in the methodological section, we model R&D-driven land augmenting technical change (aland) as a function of growth of cumulated domestic R&D stocks. Fig. 4 displays the average growth rates of aland across both baseline scenarios. This exercise allows to compare the endogenous growth rates of land augmenting technical change with exogenous growth rates that are modelled exogenously in standard baselines. This can also serve as a validation of the productivity growth rates that are usually assumed in the ex-ante projection exercises such as those elaborated in the Agricultural Model Intercomparison and Improvement Project (AgMIP, www.agmip.org), which compared agricultural output projections for a large number of global PE and CGE models (also including MAGNET) [von Lampe, [11]]. To measure technical change, AgMIP uses the so-called Intrinsic Productivity Growth Rates (IPRs), which were originally developed by IFPRI for the IMPACT model. The IPRs are commodity- and country-specific assumptions on exogenous productivity growth up to 2050, based on expert opinions concerning the future returns of agriculture R&D (see annex in Wiebe et al. [66] for more information).

The first conclusion when inspecting Fig. 4 shows that the **endogenous growth rates of land productivity are for most developing countries comparably lower than the AgMIP exogenous rates** (particularly for EU-12, China, Brazil, Central America, South East Asia and High Income Asia). In these cases, standard assumptions are too optimistic with regard to yield changes as lower value added developments in agriculture lead to lower R&D investments and lower yield growth.

4.3. Projections of agricultural production, prices and caloric consumption

An important question that arises when inspecting the evolution of land productivity is how these developments are translated in agricultural production and food security. Fig. 5 shows the index of the volume of agri-food production in 2050 compared to 2010 under the alternative baseline scenarios. It is apparent that except for Canada, the quantity of production grows lower in the Baseline Vintage Scenario, which is attributed to lower growth of land productivity compared to the Baseline Alex Scenario (as shown in Fig. 4). It is also partially attributed to indirect R&D effects through foreign trade markets and growth of agricultural prices. The largest deviations in the projected production volume occur in the regions of Sub-Saharan Africa and India which suggests that our **assumptions about future growth rates of agricultural production in Sub-Saharan Africa and India based on AgMip exogenous yield growth rates are overestimated**.

The availability of food is only one of the indicators of food security. Next to that, it is also important to assess the economic access to food in the future projections. Fig. 6 shows that the average growth rates of real agricultural prices in 2050 compared to 2010 are considerably higher in the *Baseline Vintage* scenario, compared to the Baseline Alex scenario. Particularly for the **Sub-Saharan regions, the projections are highly alarming**, as agricultural prices could grow from about 30% in case of the exogenous *aland* scenario (*Baseline Alex*) up to 80% if land-augmenting technical change is driven by public R&D investments (Baseline Vintage). **An extreme divergence in the projection of agricultural prices is found in the case of India**, where instead of a 30% decline (*Baseline Alex*), prices would grow by 40%. In most other regions, agricultural prices are projected to decline, but to a lower extent than predicted by *Baseline Alex*.

The evolution of prices in time is further depicted in Fig. 7. Whereas food prices remain stable over the whole period for high income countries including Brazil and China, prices in India and Sub-Saharan Africa rapidly diverge and escalate towards 2050.

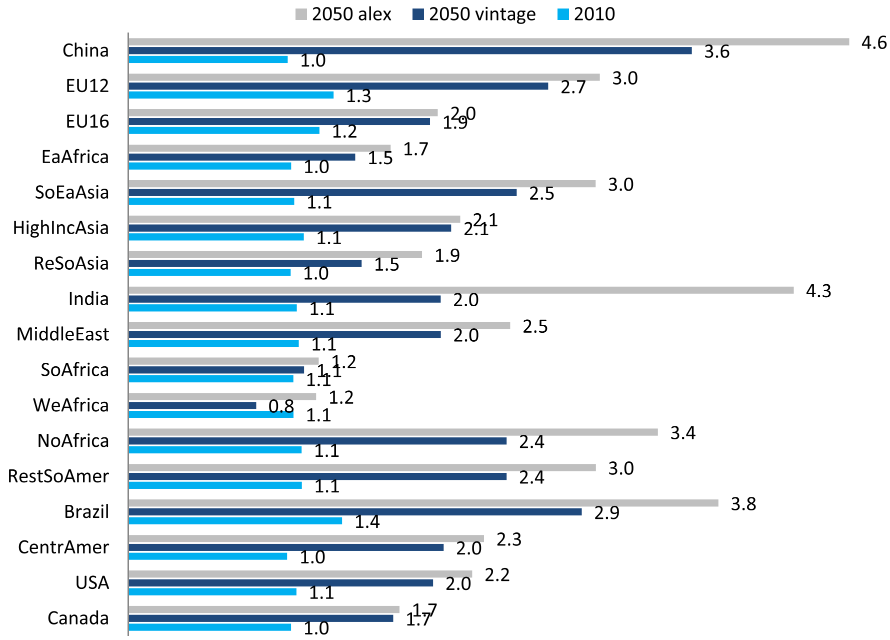

Fig. 9. Ratio of unskilled labour wages to food price index. Source: MAGNET output.

An explanation for the escalation of agricultural prices lies in the pressure on land (see, Meijl et al. [50], Schmitz et al. [67]). With increasing population growth and demand for food, the pressure on agricultural land is increasing. In some regions, the availability of agricultural land is already largely limited now, and this will be further accentuated in the future (Fig. 8). Under basically no available agricultural land, **land prices will increase dramatically and this will be transmitted to prices of food**. Interestingly, in High Income Asia where land pressure already reaches a maximum, land availability will increase towards 2050 due to declining demand for food as a result of high economic growth and negative population growth.

The access to food as one of the key dimensions of food security can also be measured in terms of income that determines purchasing power of households. As an appropriate indicator, the ratio of overall wages of unskilled labour to the food price index was chosen. Fig. 9 compares this ratio between 2010 and 2050 including also projections of standard baselines without R&D driven technical change. Results show that the **purchasing power of households dependent on low-skilled labour in Sub-Saharan Africa is expected to remain low or deteriorate**, especially in Eastern and Western Africa, where the growth of wages would barely cover the expected growth of food prices. A notable difference in projections is found in the case of India. Under the R&D driven technical change (Baseline Vintage scenario), living standards of Indian households would grow much less than in the Baseline Alex Scenario, which is driven mainly by growth of agricultural prices as nominal wages would in both scenarios grow in the same proportion. An interesting development occurs in the case of China, where massive growth of both skilled and unskilled labour wages is expected as a result of a shrinking population and high economic growth. From the food security perspective, this will be a positive factor as food accessibility will improve over time in China.

Finally, Fig. 10 shows how the excessive growth of agricultural prices is reflected in imports of calories, which shows the resilience of regions to any major food price shock. When inspecting the figures across regions, next to North Africa, Rest of South Asia emerges as a region with the highest share of imported calories. The share of imported calories is also expected to grow significantly in Sub-Saharan Africa regions, particularly in South Africa (from 9% to 16% in 2050) and in Western Africa (from 10% to 15%) and India (from 5% to 11%)

5. Discussion and conclusion

In this paper, the projections of food security towards 2050 with an R&D driven endogenous technical change were analysed. The methodological approach was based on the application of the state-of-the art CGE model MAGNET with newly built R&D module. By endogenizing R&D in global CGE models, it is possible to assess the impact of different public R&D policies on food security. Such analysis is particularly important for developing countries where food security issues are the most pertinent and public R&D plays a much bigger role in financing research than private R&D.

The findings showed that R&D growth rates at the level reached in the 2000s, particularly those for China, would not be expected any longer. Regions that might continue with high R&D investment rates are Sub-Saharan African states where rates could exceed 5% growth. As for high income countries, simulations showed that the slowdown in R&D spending which occurred after 2000 was too restrictive and there is room for boosting future R&D investments in agriculture, if we want to prevent a continuous decline in R&D stocks and productivity, as projected for the case of the USA. This is in line with the arguments of Pardey [65] who alerted that public support for agricultural science has broadly waned and an increasing share is being directed toward off-farm issues. Pardey et al. [68] warn that the increase in new funding directed to research in the New US Farm Bill is insufficient to reverse the dramatic decline in the US share of global public spending. The same applies for the EU, where in spite of the positive effort of increased financing of agricultural research in Horizon 2020 and the new European Innovation Partnership initiative in agriculture, a conflict between objectives of sustainable intensification exists (parallel advancement in productivity and sustainability) as raised by Matthews, [69]. Next to that, it must be highlighted that in the process of converting the EU and other high income regions on bio-based economies, agricultural innovation must go hand in hand with bio-industry innovations to keep up with the growing demand for bio resources.

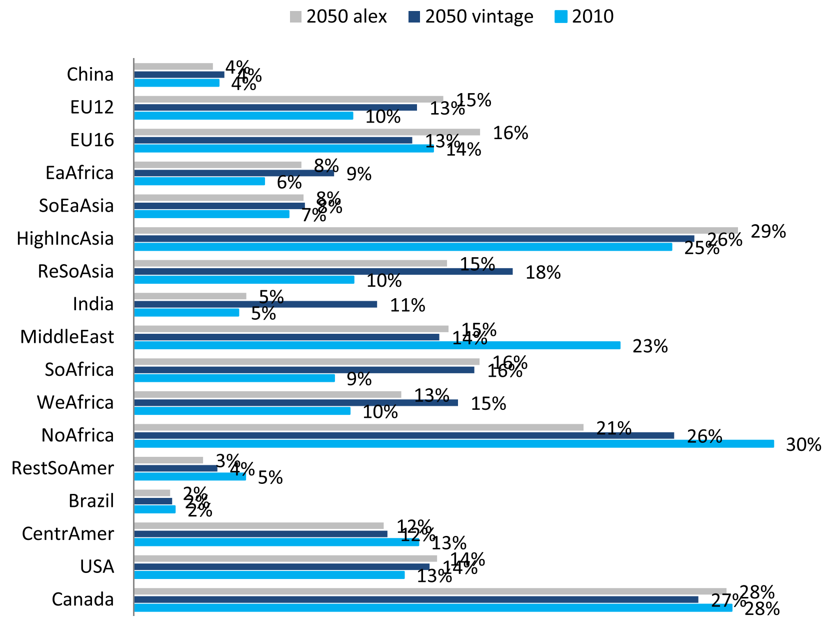

Fig. 10. Caloric dependency (share of imports of total calories consumed). Source: MAGNET output.

Concerning the impact of projected R&D investments on agricultural productivity, it was found that endogenous growth rates of land productivity are comparably lower than the standard exogenous rates based on historical projections and expert opinions. This shows that public R&D investments are not able to stimulate agricultural production to the levels that would be expected from the standard baseline outcomes used in projection studies of e.g. IPCC SSP scenarios. Regarding food prices, projections for Sub-Saharan regions are alarming. This also applies for India which clearly shows that R&D investments are not sufficient to prevent food prices from rising. As a result of that, an increased dependence on caloric imports is expected which weakens the resilience of developing regions to any food price shocks. High price volatility of agricultural crops and their relation to political instability in Africa is advocated by many scholars (see for instance Ayinde et al., [70] for Nigeria). Growth of unskilled labour wages would in some cases not adequately compensate for the expected growth of food prices which will result in the deterioration of living standards of households dependent on the income of their unskilled labour.

The policy implications following from this paper are largely directed towards higher support of national R&D investments in the developing regions. Clearly, as the most limited factor of production will become agricultural land, it will be crucial to focus more R&D investments on land-augmenting technologies, such as new seeds. As advocated by Qaim [56], GM technologies are potentially more successful in developing countries because these regions suffer more from pests and disease problems. Already now there are many interesting GM technologies tested in the field that are targeted to African agriculture such as pest- and disease-resistant rice, cassava or maize with higher nitrogen use efficiency.

Various future extensions of this research can be considered, such as the inclusion of private agricultural and non-agricultural R&D as an important determinant of productivity in high income countries and the incorporation of international R&D spillovers and diffusion of knowledge. From the policy perspective, research can be directed to estimating a desirable level of R&D investments needed to avoid adverse food security impacts of excessive biofuels policy in the future.

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Appendix A.

Table A1
Description of regions, production sectors and periods applied in MAGNET.

REGIONS	PROD. SECTORS	PERIODS	
1 Canada	1 pdr *	1 p[1]	2007–2010
2 USA	2 wht*	2 p[2]	2010–2020
3 CentrAmer	3 grain*	3 p[3]	2020–2030
4 Brazil	4 oils*	4 p[4]	2030–2040
5 RestSoAmer	5 sug*	5 p[5]	2040–2050
6 NoAfrica	6 hort*		
7 WeAfrica	7 crops*		
8 REaEurope	8 cattle*		
9 RWeEurope	9 pigpoul*		
10 SoAfrica	10 milk*		
11 MiddleEast	11 cmt		
12 India	12 omt		
13 ReSoAsia	13 dairy		
14 HighIncAsia	14 sugar		
15 SoEaAsia	15 vol		
16 EaAfrica	16 ofd		
17 EU16	17 fish		
18 EU12	18 lowind		
19China	19 oth_ser		
20 Oceania	20 oagr*		
21 RussiaStan	21 pub_ser		
	22 highind		
	23 rd		
	24 fossilfuel		
	25 CGDS		
	Total		

Note: primary agricultural sectors are noted with*. Sector description follows GTAP terminology (see sector listing at: https://www.gtap.agecon.purdue.edu/databases/v9/v9_sectors.asp).

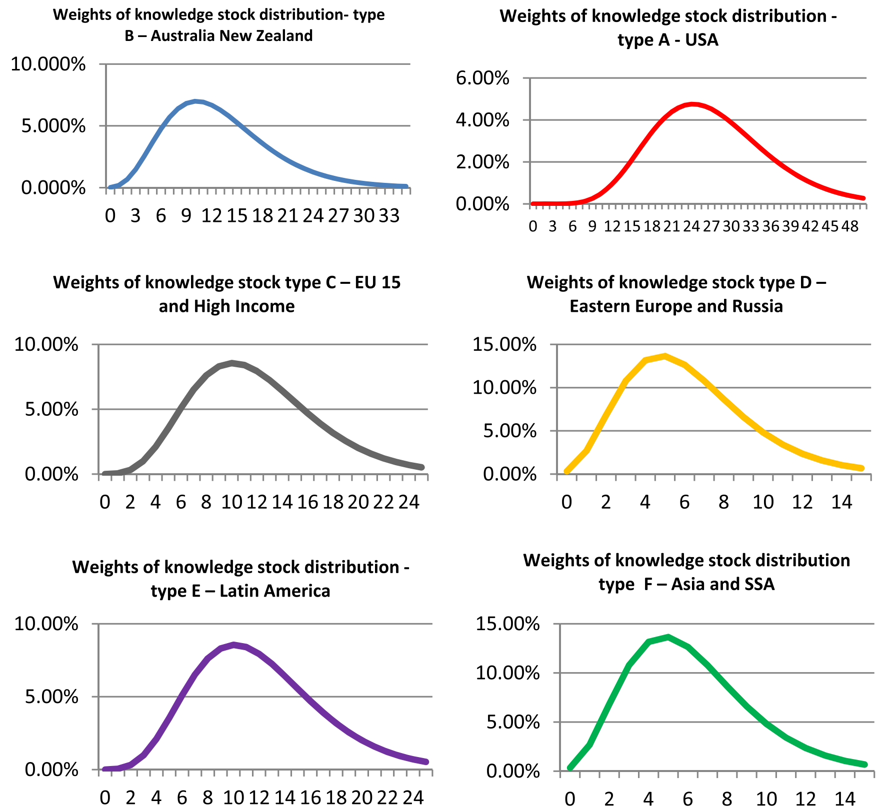

Fig. A1. Weights of gamma distribution per vintage group used in the CGE model. Source: author's elaboration.

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